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L12: Entry 1 of 16 File: USPT Nov 7, 2000

DOCUMENT-IDENTIFIER: US 6144953 A
TITLE: Time-constrained inference strategy for real-time expert systems

Application Filing Date (1):
19860520

Detailed Description Text (26):
CONFIDENCE RATING: The inference rules associated with the assignment function may themselves contain uncertainty. A numeric procedure has been developed to indicate the confidence rating of the expert in each particular assignment function. The confidence rating is a number between 0 and 1 associated with each assignment function to indicate the degree of belief in the consequent when the antecedents are known to be true (i.e. one--see Cohen, P. R., and Grinberg, M. R., "A Theory of Heuristic Reasoning about Uncertainty", A. I. Magazine, Summer 1983, which is hereby incorporated by reference). These confidence ratings are combined and propagated through each consequent assignment function. This use of a confidence rating is similar to the use of a certainty factors in the MYCIN system (e.g. see B. G. Buchanan et al, Rule-Based Expert Systems, Addison-Wesley 1984). A generalization of Bayes' theorem is utilized to derive the confidence rating of nodes in the inference network. Whereas Bayes' theorem requires masses of statistical data, the generalization of this theorem utilizes subjective expert judgment in its place. Thus the domain expert must initially specify the confidence rating of each node. This relaxation of Bayes' theorem requires that the domain expert be consistent and accurate in assignment of confidence ratings throughout the network.

Detailed Description Text (34):
In the absence of any knowledge about the probability distribution of node values, a default value of 0, representing complete uncertainty, should be chosen. In a boolean logic system nodes would have only two possible values, representing true or false. In a bayesian system, the equivalent values would be 1 or -1, with no in-between values. The bayesian system allows for in-between values as a way of representing uncertainty, but the underlying concept is essentially binary.

Detailed Description Text (36):
The above statement says that the expected change is 1 because there is a 50% probability of a value change (from the default value) of 0 to -1; and there is a 50% probability of a value change from 0 to 1. In either case, the absolute value of the change is 1.

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L15: Entry 7 of 38 File: USPT Sep 12, 2000

DOCUMENT-IDENTIFIER: US 6119103 A
TITLE: Financial risk prediction systems and methods therefor

Application Filing Date (1):
19970527

Brief Summary Text (13):
The account issuers themselves also developed techniques to gauge the credit worthiness of a particular potential or current account holder based on how that account holder pays on an account. By way of example, behavioral scoring systems may be employed to monitor the payment performance of an account (e.g., by monitoring the payment data and the relationship between credit line and balance) in their assessment of an individuals credit worthiness. However, since the payment performance of an account is updated only per billing cycle, this technique also typically does not provide adequate warnings pertaining the financial risk of a particular account holder based on activities occurring in more recent history. By way of example, if an account holder's past payment performance on an account has been satisfactory, he may, in the last few days, use up substantially all the available credit of one or more accounts (thereby putting him at a higher financial risk) without triggering an alert from the account issuers' payment-based scoring systems.

Brief Summary Text (18):
In view of the foregoing, there are desired improved financial risk prediction systems and methods therefor which minimize financial losses to the account issuers and/or account holders. The improved financial risk prediction system preferably employs data that facilitates timely warnings of potential financial risks to the account issuers to enable the account issuers to take steps in time to minimize further financial losses. The improved financial risk prediction technique more preferably provides the aforementioned timely warnings at the account holder level, thereby advantageously enabling a given account issuer to ascertain the credit-worthiness of a particular account holder and to take steps to protect outstanding credit lines even if, for example, the financial risk is assessed on transactions performed on accounts belonging to other account issuers.

Detailed Description Text (41):
The predictive model may consist of model metadata (which may represent pattern weights, calibration factors, and other data which characterizes and conditions the functionality of the predictive model), along with the segmentation rules, exclusion rules, selected paterns, and reason codes that define the model. In one embodiment, the predictive model may, for example, include model cubes and model profiles. Model cubes are model definition and characterization data, and may contain summarized dimensional data (i.e., Merchant Category Code or "MCC", country, zip, MCC-country, MCC-country-zip, and the like) used by the predictive models. Model cubes may also contain the metadata (e.g., the pattern weights), and the basic descriptive data. The model cubes (so called since they contain multi-dimensional data) may be implemented as RAM-cached multi-dimensional databases of summarized dimensional data and the metadata that supports the predictive model. Model profiles represent profiles for tracking historical model-generated information pertaining to a given account. In one embodiment, model profiles

represent cumulative values of model

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L15: Entry 13 of 38 File: USPT Aug 17, 1999

DOCUMENT-IDENTIFIER: US 5940811 A
TITLE: Closed loop financial transaction method and apparatus

Application Filing Date (1):
19961015

Detailed Description Text (12):
The applicant's credit report is obtained from the credit bureau by transaction processor 10, evaluated using an underwriting model 90, to be described more fully below, and a decision is made based on the results of the evaluation by underwriting model 90, which results are in the form of a score and an associated risk factor, to grant or deny the loan or credit card application. Transaction processor 10 informs the borrower of the decision and, if the application is granted, presents the terms of the financial transaction to the applicant via monitor 50. If the borrower accepts the terms of the loan or credit card, the borrower can sign the documents electronically using an electronic signature pad 100 on kiosk. The same approach can be used to verify in writing the fact that the borrower understood the terms of the loan or credit card, as required by law, or, if the loan or credit card is denied, that the borrower received a copy of the negative determination letter with its explanation as to why the application was denied. In each case the consumer's signature on the documentation can be secured electronically.

Detailed Description Text (15):
Underwriting model 90 is established by first identifying criteria that might have a bearing on the ability and willingness of the borrower to repay the loan or credit card. Then historical data is gathered to determine the influence, or weight, to be given to each criterion. The data is examined and the initial set of weighting factors are applied to develop estimates of the actual outcome of the data. The model's estimates are compared to the actual outcome, and the weights are adjusted to make the estimates closer until the outcome predictions have been optimized. Underwriting model 90 uses information calculated from the credit report, such as the ratio of debt to liquidity. An underwriting model designer will also make a judgment on how few criteria are needed to make a sufficiently accurate prediction. There are commercially available computer programs, known to those skilled in the art of computer decision-making, that can be used to develop underwriting models for the lending model upon entering the criteria and initial weighting factors.

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L15: Entry 19 of 38 File: USPT Nov 3, 1998

DOCUMENT-IDENTIFIER: US 5832465 A
TITLE: Method for building a self-learning evidential reasoning system

Application Filing Date (1):
19970407

Detailed Description Text (8):
In the spreadsheet of FIG. 3a, the output processing node is credit worthiness. The possible set of linguistic evidential values for the credit worthiness output processing node are "strong", "medium", and "weak". A number of different examples are then entered into this spreadsheet by the experts. The examples are represented in this spreadsheet as deals. In FIG. 3a there are 41 different examples. The experts review each of the examples and determine what the credit worthiness (i.e., the output) of the example is. For instance, deal number six has a "medium" evidential value for the employment stability input node, a "high" evidential value for the residence stability input node, a "poor" evidential value for the income: ability to pay input node, a "poor" evidential value for the credit history input node, and a "poor" evidential value for the severe credit opinion input node. The experts after weighing these evidential values decided that the credit worthiness of this particular example is weak. Each of the remaining examples in FIG. 3a are analyzed by the experts in the same manner as in deal number six, i.e., weighing the input linguistic evidential values and determining the credit worthiness.

Detailed Description Text (12):
The linguistic evidential output value from each input processing node in the input layer is then inputted to the output layer processing node (i.e., credit worthiness), where the linguistic evidential values generated therefrom are translated to a numeric value. Again, the evidential numeric values correspond to the linguistic evidential values and have values ranging between -1.0 and 1.0. One possible example of an evidential translation for the credit worthiness processing node is if the linguistic evidential data for the employment stability node is "medium", then the numeric evidence value is 0.1. If the linguistic evidential data for the resident stability node is "high", then the numeric evidence value is 0.5. If the linguistic evidential data for the income:ability to pay node is "poor", then the numeric evidence value is -0.3. If the linguistic evidential data for the credit history node is "poor", then the numeric evidence value is -0.3. If the linguistic evidential data for the severe credit opinion node is "poor", then the numeric evidence value is -0.3. After the linguistic evidential values have been translated to numeric values, then the values are aggregated to a final evidential output value using an evidence aggregation function. The aggregated evidential value will also have a value in the range between -1.0 and 1.0. Next, the evidential aggregation value is mapped to a linguistic evidential value using a mapping function. One possible mapping for the credit worthiness output processing node is if the aggregate evidential value is greater than 0.7, then the linguistic evidential output value is "strong". Other possible mappings are if the aggregate evidential value is between -0.6 and 0.7, then the linguistic evidential output value is "medium" and if the aggregate evidential value is less than -0.6, then the linguistic evidential output value is "weak". Essentially, the final linguistic evidential output value recommends whether the financial service application should be accepted or denied.

Detailed Description Text (16):
In order to overcome any weaknesses or inefficiencies during the translation of the linguistic evidential values to the numeric values at the inputs of the input layer processing nodes and the mapping of the aggregate numeric value to the linguistic evidential value at the output, this invention combines the numeric to linguistic evidential value mapping at the output of the input layer processing nodes with the linguistic evidential value to numeric translation at the input of the output layer processing node. This is achieved by using a weighting function, S, that is placed after the evidence aggregation function. This rearrangement is possible since the example-based evidential reasoning system 10 is a tree structure rather than a network structure. With a tree structure, the outputs of the input layer processing nodes are fed to one input of the output layer processing node. In order to map the numeric value to a linguistic evidential value and translate the linguistic evidential value to a numeric value, the weighting function, S, is a stepwise function. In general, the weighting function, S, is a transformation (i.e., linear or nonlinear) from the [-1,1] space to the [-1,1] space. The parameters of the weighting function, S, are called weights, denoted by w. The input of the weighting function S is denoted by .theta., which is the aggregated evidence value. FIG. 6 shows the weighting function, S, in use with the model structure 24 in both the input layer and the output layer.

Detailed Description Text (18):
The gradient descent optimization attains a weight vector that minimizes the error surface, E. One simple applied descent method is a stepwise gradient descent, where given an initial starting position in weight space, the next position would be a constant proportion of the gradient at the current position, and in the negative direction of the gradient, from the current position. The stepwise gradient descent method iterates repeatedly until a stopping criteria (e.g., gradient is smaller than a constant) is reached. Therefore, any weight function S.sub.i with parameters w.sub.i1,w.sub.i2, . . . is defined as: ##EQU9## The above gradient descent optimization can be summarized as follows: ##EQU10## The above-defined evidence aggregation function and the weighting function form a numeric to numeric system. These functions enable the linguistic based examples gathered from the experts to be converted to numeric values for self-learning purposes. Thus, for each linguistic output from a processing node in the model structure a distinct numeric value between -1.0 and 1.0 is assigned. Through self-learning the weights in the weighting function, S, are adjusted to best approximate the assigned numeric value. For each linguistic input in a processing node, a distinct numeric value between -1.0 and 1.0 is assigned. A extra node having a single input is placed between the input and the system and is shown in FIG. 6. Since the evidence aggregation function has only one input, the assigned numeric value passes through unchanged to the weighting function. Through self-learning, the weights in the weighting function are adjusted to best transform the assigned numeric value to a linguistic evidence value.

Detailed Description Text (21):
The linguistic evidential values for each of these attributes in the input processing nodes are shown in the value column of FIG. 7. These values are translated to numeric values and are shown in the input column. The aggregated evidential value for each input processing node are shown in the evidence column. The value that is outputted from each of the input layer processing nodes are shown in the output column. These values are used as inputs to the output layer processing node. The aggregated evidential value for the output processing node is shown in the evidence column under the second level node. The value that is outputted from the output layer processing node is shown in the output column in the bottom right hand corner of FIG. 7. In this example, the application has an output 0.98308, which is an indication of strong credit worthiness. Using the example-based reasoning system 10 to review a financial service application enables the application to be analyzed with a decision approving or rejecting the

application within a few minutes, as opposed to 15-45 minutes associated with the traditional approach of evaluating an application.